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Keith Pavitt and the Invisible College of the Economics of Technology and Innovation

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Abstract

This paper uses a database on scientific interaction in the field of the economics of technological change and innovation. The database is used to address two issues. First, the network is shown to be (approximately) scale-free. This suggests that growth of the number of scholars active in the field and so-called preferential attachment (i.e., scholars entering the field prefer to attach themselves to highly reputable existing members of the network) are characteristic of the nature of the underlying field. Thus, increasing returns seem to govern mechanisms of reputation formation. Second, the potential existence of cohesive subgroups of relatively strongly connected scholars is explored, and the implications of this for the paradigmatic structure of the field are discussed.

Keywords: Scale-free networks; Scientific interaction; Evolutionary economics; Innovation studies

1. Introduction

Innovation is now at the centre of policy thinking in modern developed societies, but we must not forget that the study of innovation as an economic phenomenon is a relatively recent development. Traditional economics largely took science and technology as an exogenous phenomenon, not in need of explanation or detailed study. But following the pioneering contributions of Joseph Schumpeter during the first half of the 20th century, a new school of economic thinking emerged both in the USA and in Europe from the 1960s onwards. In this emerging body of literature, science, technology and innovation were seen as phenomena that are endogenous to the economy, i.e., they are important factors in determining economic change in the broadest sense, but are also the result of economic forces. At the same time, it was recognized that the existing economics toolbox, based on such assumptions as equilibrium and full rationality, is not particularly suited to analyze innovation. A preliminary hallmark of this 'new'

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Economics of Technology and Innovation is in Dosi et al. (1988).

Rather than being concerned with the actual content of the work in the new Economics of Technology and Innovation, this paper will attempt to answer some questions with regard to the structure of collaboration and interaction between contributors to this new and emerging field. We employ a dataset that provides a unique insight into how personal relationships in this dynamic field have been developing. The data are used to investigate two research questions. The first one deals with the role of a selective group of 'intellectual leaders' in connecting the research network. Using a generic mechanism of network formation (so-called preferential attachment), one may derive a testable hypothesis regarding the identification and role of these intellectual leaders, and this is applied to our dataset.

The second research question deals with the structure of the field in terms of sub-communities. Even a superficial impression of some of the discourse in the field suggests that strongly different points of view exist with regard to the fundamentals of the approach. Our database describes a network of professional contacts between scholars in the field, and it seems plausible that the nature of these relationships is causally related to the observed differences in fundamentals. One hypothesis is that subgroups in the network are formed around these central opinions, leading to a division of the total network into factions.

Over the years, many important scholars have contributed to this emerging field of study. Keith Pavitt was certainly amongst the most prominent contributors to the field. He was a pioneer in many senses, for example, by working on many diverse subfields, such as management studies, macroeconomics and international trade, science and technology indicators, etc., and by drawing together insights from all of these. The database on which this paper draws was collected in an online survey among scholars in the field of the Economics of Technology and Innovation (Verspagen and Werker, 2003, provides a basic description of the empirical results of the survey). Keith Pavitt submitted his answers to the questionnaire on 24 November 2002. The results that are presented in this paper bring out Keith's unique role as a source of new ideas, inspiration, scholarly advice, supervision, and, for those who actually interacted with him on a personal level, friendship.

In laying-out the results of the survey and analyzing the research questions, this paper will illustrate the role of Keith Pavitt in the field of the Economics of Technology and Innovation with some empirical data describing the network of scholars in this field. The database brings out the important and leading intellectual role of a limited group of scholars in the field. However, with the exception of Keith Pavitt, the results will be presented in an anonymous way, so that the exact identification of the 'hall of fame' will leave something to the imagination of the reader.

The rest of this paper is structured as follows. The next section will present the theoretical background of the analysis, and two specific research questions. Section 3 describes the way in which the data were collected. Section 4 addresses the first of our research questions, which is concerned with the nature of the field of the economics of innovation and technology as an emerging scientific discipline. Section 5 addresses the issue of community-building in the emerging field, which is the topic of the second research question. The identification of so-called cohesive subgroups in the network will be attempted using tools from social network analysis. Section 6 gives the conclusion.

2. Research questions and theoretical background

As in much of the recent analysis of scientific communities (e.g., Newman, 2001; Hummon and Doreain, 1989; Wagner and Leydesdorff, 2004), this paper views the progress of scientific disciplines as crucially dependent on the network structure among the scholars active in it. This is rooted in the notion that important theories and ideas, as well as the empirical testing of these, develop as a collective effort, in which contributors draw importantly on each other for inspiration, idea-generation, data development, etc. Most of the work in this tradition (e.g., Granstrand, 1994, for a case concerned with the same field of study as the current paper) has been based on co-authorship or citation links as the data source for empirical analysis, i.e., formal and codified publications have mostly been used to describe the network structure of scientific fields.

However, networking in science is about more than just publishing together and citing other scholarly work (Crane, 1972). Informal interactions at various frequencies and in various forms (e.g., from corridor discussions to e-mail exchanges to keynote speeches at important conferences) are just as much a form of networking between scientists as formal publications. For certain types of interaction, these informal channels are the only possible way of communication. The survey that will be described in the next section is an attempt to 'codify' the network links in the field of the economics of innovation and technology that exist outside formal publications.

Various formal models have been proposed in the literature to analyze networks in general, and networks of scientific collaboration in particular. The most basic model, due to the work by Erdös and Rényi (see, Bollobás, 1985 for a summary), is one in which a fixed number of actors ('nodes') exists in the network, and in which connections between these actors can be on or off with a fixed probability. Barabási and Albert (1999) proposed to take the statistical distribution of 'connectivity' among nodes in the network (in the case of networks of scientific collaboration: scholars) as a sort of 'universal quantity' that can be used to characterize different types of networks. In particular, they observed that many empirical networks are characterized by a so-called power-law distribution of connectivity among the nodes. In technical terms, this means that the probability, denoted by $P(k)$, for an actor to be connected with degree k follows a distribution $P(k)\ Ak^{-\gamma}$, where A and γ are parameters.

k_i is usually measured by the number of nodes to which a node i is directly linked (so-called degree centrality). The power law characteristic then says that, when plotted on a log–log scale, the frequency distribution of connectivity over the nodes is a straight, downward sloping line. Particular values of the slope of this line (γ) are associated with particular features of the network, such as its 'robustness to attack' (i.e., the random elimination of nodes) (see Dorogovtsev and Mendes, 2002, for a discussion of this).

However, Barabási and Albert (1999) and Barabási et al. (1999) also observed that the traditional theory of random graphs (as formulated by Erdös and Rényi) does not lead to a power law distribution of connectivity. They suggested a new model of network formation, which does lead to the observed power law distribution of connectivity. This model has become known as the model of 'scale-free networks'. Two assumptions are crucial in this model: positive network growth (in terms of the number of nodes) and the formation of links must go hand-in-hand, and the choice of links that connect new nodes to the network must be based on a mechanism called 'preferential attachment'.

The first of these assumptions is an alternative to the assumption made in random graph theory that one starts with a fixed number of nodes, and then connects these nodes at random. In the model of scale-free networks, new nodes are added to a pre-existing network, and each new node may connect to m other (pre-existing) nodes (m is the only parameter in the model of scale-free networks). The second assumption above says that the probability for a new node to connect to any pre-existing node is proportional to the connectivity of that pre-existing node. In other words, new nodes prefer to attach to existing nodes that are already well connected. In terms of the networks of scientific collaboration that are the topic of this paper, this assumption may be interpreted as saying that scholars who are entering a field prefer to be connected to scholars who already have a high reputation. This is reminiscent of the so-called 'Matthew effect' of scientific reputations (Merton, 1973). The simple behavioural rule of preferential attachment in combination with network growth leads to ordered patterns at the aggregate network level (such as the observed power law), suggesting self-organizing behaviour (see Dorogovtsev and Mendes, 2002, for a discussion of the self-organizing nature of scale-free networks).

The power law distribution of connectivity in these scale-free networks says that the large majority of nodes in the network have low connectivity. A small number of nodes, i.e., these to which new nodes prefer to connect, have very high connectivity. In other words, the scale-free networks are characterized by a skewed distribution in which only a few network nodes stand out in terms of connectivity, or, if one is willing to take this as an indicator of scientific quality, scholarly reputation.

The first research question of this paper, which will be explored in Section 4, is whether or not the network of interaction that we observe in the field of the economics of innovation and technology can be characterized as a scale-free network. If this is the case, i.e., if we observe a power law distribution of connectivity in the network, this would be an important indication of the importance of network growth combined with preferential attachment as factors in the network dynamics.

Anticipating such a positive answer to this question, the analysis will also ask whether Keith Pavitt can be observed to be one of the highly connected scholars to whom new network members preferred to connect.

The second research question that will be addressed is rooted in the theory about scientific communities. The field of the economics of innovation and technology emerged, at least partially, as an alternative to mainstream economics. The latter discipline looked at innovation and technology as exogenous phenomena, not central to the core of the field. Throughout the contributions of, for example, Freeman (1982), Nelson and Winter (1982), Dosi et al. (1988, 1990) and Freeman and Soete (1997), is a strong criticism of the mainstream economic analysis of technological change and innovation. Central issues in this critique are the non-equilibrium nature of economic change, the boundedly rational basis of economic behaviour and the use of heterogeneous agents as a tool for analysis. From this point of view, it has been suggested (for example, in the references above), that an evolutionary theory is a better basis for the economic analysis of innovation and technology than the mainstream neo-classical theory.

A (superficial) reading of this critique suggests a state of affairs that is reminiscent of a process of competition between two alternative paradigms of scientific progress, as analyzed in the work of Kuhn (1962). In such a view, the newly emerging "evolutionary economics" would present itself as an alternative for mainstream economics, with as the most important element a more explicit role for technology and innovation in the theory. In line with the Kuhnian tradition of Scientific Revolutions, we might then expect a clash of opinions between mainstream and evolutionary economics.

An alternative hypothesis is to expect convergence between the two streams once ideas are cross-fertilizing in the network structure of scientific collaboration between scholars in both traditions. Mainstream economists, evolutionary economists and other 'heterodox' economists meet at conferences, use similar data sources, sometimes publish in similar journals, and discuss similar issues. Hence, some observers have asserted that the boundaries between the two streams are becoming increasingly fuzzy. For example, Heertje (1993) argued:

"neo-Schumpeterians [i.e., the evolutionary tradition] have been productive in their criticism of the neoclassical scheme on the basic of an evolutionary approach, but the questions they have raised have been addressed more or less successfully by many scholars, who have close links with the neoclassical tradition (. . .) I would not be surprised to see the present Schumpeterian mood to be part of mainstream economics before the end of this century" (p. 273–275).

Being already at the beginning of a new century, the second research question asks to what extent the field of the economics of innovation and technology can be characterized as one in which competing subgroups are identifiable. A subquestion to this is the extent to which the label of "evolutionary economics" is useful for describing at least one possible core of the emerging field. Methods from social network analysis will be used to answer this research question. These methods will be aimed at identifying so-called cohesive subgroups, i.e., subgroups of interacting scholars who are particularly densely connected relative to outsiders to the subgroup. The question that will be asked using these methods, is whether more than one such cohesive subgroup can be identified in the network.

3. The survey methodology

To get closer insights into the composition of the broad and diverse group of economists working in the field of "Innovation and Technological Change", like Crane (1972), a survey was conducted in the research community under study. The survey takes a distinctly different approach from the bibliometric analyses mentioned above and comes closer to the 'social network' (e.g., Wasserman and Faust, 1994) and the 'social capital' (e.g., Lin, 1999) approaches. The survey was conducted among scholars in the field of the economics of innovation and technological change and/or evolutionary economics, and was aimed at mapping the intellectual relations between people active in the field. In particular, we interpret the 'Invisible College' (a term borrowed from Crane, 1972 and Merton, 1973) that we are analyzing as a social network in which both strong and weak ties (Granovetter, 1973) play a role. Following Crane (1972), strong ties (e.g., between Ph.D. student and supervisor, or between co-authors) may be important for the formation of intensive knowledge networks in which the main ideas of a new field are created. Weak ties (e.g., inspiration through the written literature) may be more important for the diffusion of these ideas to a wider research community.

The survey was set up specifically to identify weak and strong ties (see also Table 1). Respondents were asked to list people who had influenced them. Six categories of people were asked for: the respondent's Ph.D. supervisor, his/her Ph.D. students, his/her co-workers (defined as people working in the same institution), his/her co-authors (outside the respondent's main institution), his/her network contacts (defined as people who the respondent meets regularly at conferences, workshops, etc.) and, finally, his/her sources of inspiration (important scholars whose work the respondent knows, but whom he/she has never met, an important group in this category are scholars from the past who are no longer active).

Respondents were asked to list at most five people in each category, with the exception of the Ph.D. supervisor, which could only be one name. Names could be based on the entire career of an individual, not only the state of affairs at the time of the survey. If more than five people qualified for a category, only the five most important persons (in terms of the quality of their contribution) were asked for. The categories were presented in the order mentioned in the text above, where the interpretation is that earlier categories imply stronger links. The instructions stipulated that if a person qualified for one category, (s)he could no longer be entered in a later category, even if (s)he was not listed because (s)he was not among the five most important people in the category. In this way, respondents were forced to report on a broad range of contacts in the continuum of strong links to weak links.

The survey was sent to all people who appeared in the reference list of a recent overview paper of the field (Dosi et al., 2002). As explained above, the respondents were asked to give the names of researchers with whom they have the aforementioned relationships. E-mail addresses of the people listed were asked for, but this was indicated as optional. For names that were reported without an e-mail address, a search for the e-mail address was performed on the Internet. Everybody mentioned in the responses was also sent an invitation to fill in the survey (this corresponds to the name generator mechanism in Lin (1999)). The survey was kept running in this fashion, and the results reported in this paper correspond to the database at 5 November 2003. At this point, there were 2850 names in the database, of which invitations to fill in the survey had been sent out to 1859 persons (no e-mail address was available for the remaining persons). Six-hundred-and-seventy-seven responses were obtained (36% of the invited people, 24% of the total). The results reported in this paper are based on the database consisting of these 677 respondents, plus 136 additional persons. The majority of these 136 persons consist of scholars who could not fill in the survey (most often because they were deceased at the time the survey went out), but who were listed by other respondents.

Table 1
Relationships between researchers and the quality of their ties

Relationships	Maximum number	
Inspiration	5	Ties between researchers becoming stronger ↓
Network	5	
Co-authors	5	
Co-workers	5	
Ph.D. students	5	
Ph.D. supervisor	1	

We have little or no information on the representativeness of our sample for the total group of scholars in the field. Possible sources of bias in the sample may be that we started the name generator procedure from a single paper, and that the invitation to participate in the survey was signed by ourselves. The particular start of the name generator mechanism (Dosi et al., 2002) was chosen because it is recent, was drawn up by experts in the field and because it refers to the work done by researchers from all kinds of backgrounds. The fraction of respondents in the final sample that stems from this 'first generation' is rather small. Hence we have little reason to suspect that the bias related to this is large. The second source of bias is potentially more important, since respondents might consider ourselves to be associated to a particular 'school of thought', and this may influence the willingness to participate in the survey. Until we have an opportunity to test the representativeness of our sample against a more objective source of information, there is little that we can say about the impact of this (one may note that even a bibliometric search, as a source of comparison for our sample, may be biased by the nature of the journals included in specific databases).

We will thus have to be careful when interpreting the results.

4. The 'Invisible College' as a scale-free network

As a prelude to the more formal analysis of the database, Fig. 1 provides an impressionistic picture of the network structure. For the occasion, network nodes (i.e., scholars active in the field) have been colored according to their 'distance' from Keith Pavitt. A distance of one would indicate a direct relation with Keith Pavitt, a distance of 2 would indicate a relation through one intermediate, etc. The top panel graphs the network based on all relationships, covering the whole spectrum from strong to weak ties as explained in Table 1. The bottom panel eliminates all network links based on the weakest links, i.e., sources of inspiration without the two linked people knowing each other personally (so-called 'frame of reference'). The network layout was obtained using a 'spring embedding' or 'Gower scaling' method in UCINET 6.0. The input data is a binary matrix of relations on the basis of the survey database, which was made symmetric by assuming that a link exists when at least one of the two scholars involved reports it. The method used plots close together those network members who have intense relations, either directly, or through other network members. However, the method is impressionistic, and at the level of individual network members, positions may be subject to significant stress (mismatch between true distances and distances in the two-dimensional plane).

The pictures bring out the network of scientific interaction as one that is densely connected. Distances in the network are relatively small, as indicated by the 'distance from Keith Pavitt'. In the top panel, this is at most 6 degrees of separation, in the bottom panel it is at most 7. But the majority of network members are at a much closer distance to the centre: virtually everybody (98% of all network members) is within a distance of 4 (top panel) or 5 (bottom panel). A large number of network members have a direct link to Keith Pavitt, as indicated by the red dots in the top and bottom panel. This indeed identifies Keith Pavitt as one of those scholars with very high connectivity, as predicted by the scale-free network model. Finally, the two pictures show that the structure of the network depends on which type of links (on the scale from weak to strong links) are considered: when the weakest links are left out, the network structure, at least at an impressionistic level, changes into one with a stronger core/periphery distinction (as indicated by the long 'tail' in the bottom panel versus the more concentric structure of the top panel).

In order to provide a more direct and formal indication of the extent to which the scale-free network model is a relevant description of the networks in Fig. 1, the distribution of connectivity is studied in more detail. Because each respondent to the survey could list 26 direct contacts at most, the distribution of so-called outward degree connectivity (i.e., the number of people listed as contacts by the respondent) is potentially truncated. Note that this does not hold for inward degree connectivity (the number of times somebody is mentioned). Nevertheless, the choice was made to focus on a slightly more sophisticated indicator of connectivity, the so-called betweenness centrality. Goh et al. (1999) suggest this measure as one that may be better associated with scale-free networks as a 'universal quantity', and show that under the assumptions of scale-free networks introduced above, the betweenness centrality also follows a power law distribution.

Betweenness centrality conceptualizes connectivity by using the notion of shortest paths (*geodesics*) in the network. A geodesic between two nodes in the network is defined as the path that covers the least possible intermediates between the two nodes. Note that there may be more than a single shortest path between any two nodes in the network. We indicate the number of geodesics between two nodes i and j by $C(i, j)$, and the number of these that run through node s (not equal to i or j) by $C_s(i, j)$. Then the betweenness centrality of a node s, denoted by g_s, is equal to $g_s = \sum_{i\neq j} C_s(i, j)/C(i, j)$. Thus, this definition measures the connectivity of a node by the number of times it lies on a geodesic between other nodes of the network. In the calculations, the measure will be standardized by expressing it as a percentage of the maximum attainable betweenness centrality given the network structure.

Fig. 2 plots the probability distribution of betweenness centrality in the networks based on the survey data. The top-left panel corresponds to the same network as in the top panel of Fig. 1, i.e., incorporating all reported linkages. The top-right panel corresponds to the

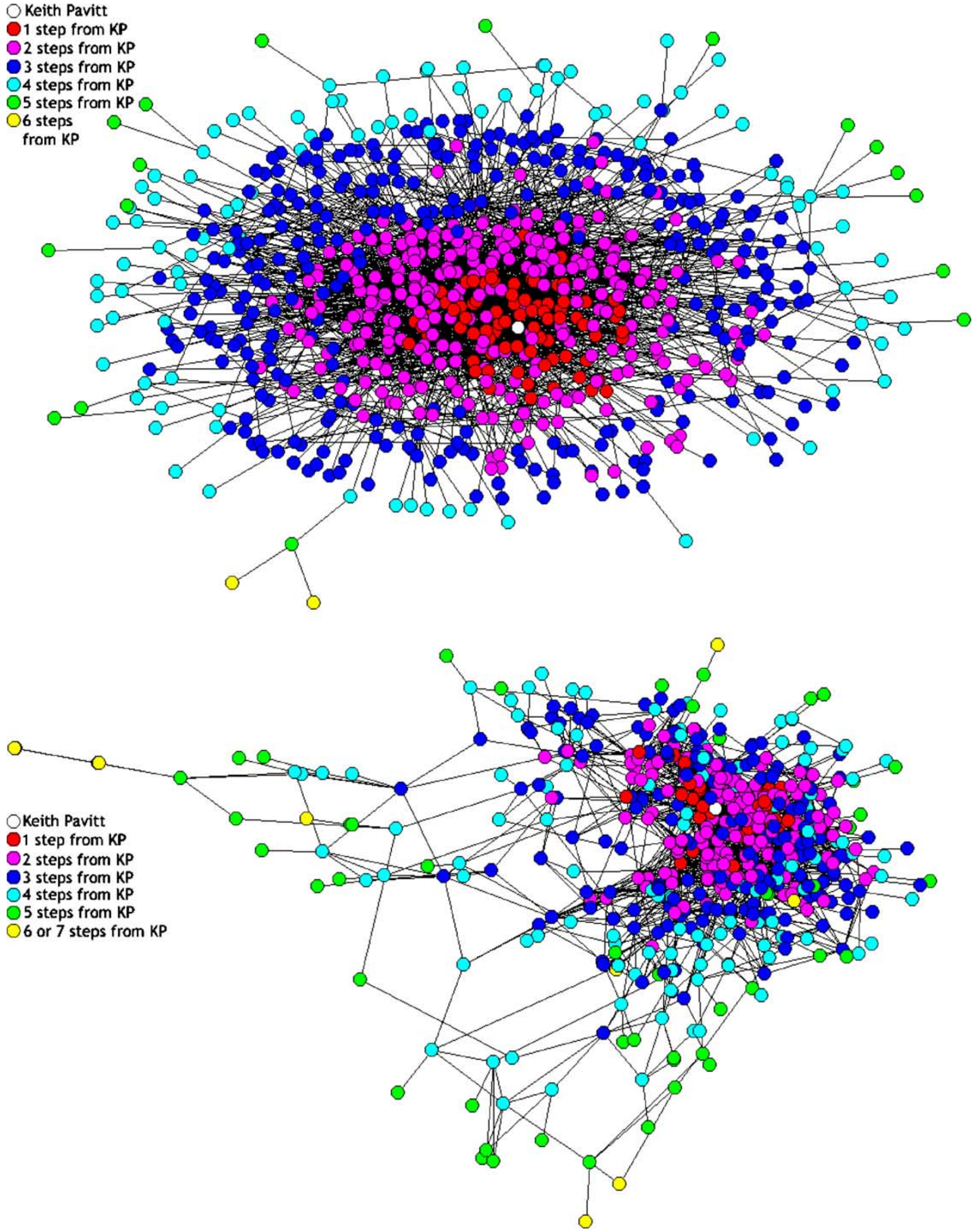

Fig. 1. An impressionistic picture of two layers of the network based on the survey database; colors indicate network distance from Keith Pavitt.

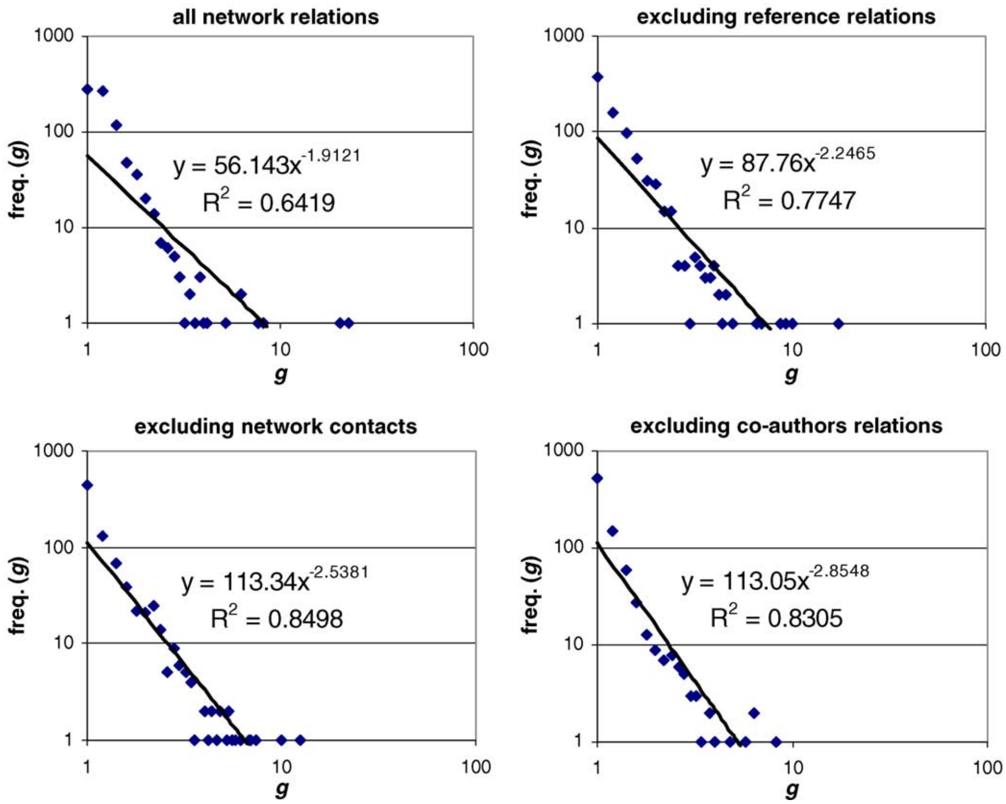

Fig. 2. Empirical (dots) and fitted (lines) probability distributions of betweenness connectivity in the database networks; at various 'layers' of the network (intensity of links), the pictures delete successive layers of weak/strong links, starting with the all links, and then deleting the weak links one at a time; all distributions show an approximate power law distribution, suggesting that the networks are indeed scale-free networks.

same network as in the bottom panel of Fig. 1, i.e., leaving out from the first network all linkages based on 'frame of reference' only. The result is a network that is based purely on personal interaction (of either the weak or strong type). The two pictures in the bottom panel of Fig. 2 delete, successively, two additional 'layers' of network links: first (left-bottom) all linkages based on contacts at conferences, workshop, e-mail, etc. are deleted ('network contacts'), so that only linkages between co-authors or co-workers remain; second (right-bottom) all linkages based on co-authorships outside the respondent's main institution are deleted (so that only contacts with scholars who were at some point at the same institution remain).

It is striking that all four panels of Fig. 2 show an approximate power law: the distribution (plotted in double log space) appears linear, as indicated by the straight lines (which are fitted through least squares). The fit is not perfect, and in particular a number of points at the right side of the distribution are off the linear relationship. In particular, the right side of the distribution seems to be characterized by a rather sizeable variation around the supposed power law. If anything, there is an indication that the tails of the distribution are somewhat fatter than a pure power law. This pattern is similar to the one observed for networks of co-authorship relations in scientific publishing, reported by Wagner and Leydesdorff (2004), who suggest that, in their network, the right tail of the distribution displays peculiar dynamics, in which competition plays a lesser role than in other parts of the distribution. We have no indication that this is similar in our network. Instead, the results might be partly related to the larger impact of random noise, given the very low frequencies (typically 1 or 2, we only observe integer frequencies) at this end of the distribution.

Despite the imperfect fit, the results suggest that the structure of the networks under consideration emerges as a result of network growth (a growing number of scholars working on innovation and technology) coupled with preferential attachment (i.e., new network members want to link to existing scholars with a high reputation). This conclusion seems to hold for all four networks, i.e., the scale-free property is robust for the elimination of various degrees of weak links in the network. Moreover, the coefficients of the estimated regression lines suggest that when weaker links are deleted from the network, the scaling parameter γ, which measures the absolute value of the slope of the distribution, increases. This is a preliminary result that needs to be substantiated by more robust estimation techniques, but it may indicate that some properties of the network evolve with the level of weak/strong linkages.

Note that we have not performed any direct test of the preferential attachment mechanism, and hence the evidence supporting this is at best circumstantial. The power law result suggests that implementing a more direct test of the preferential attachment mechanism in networks like ours would be a useful undertaking. As an alternative 'explanation' of the power law result, one may put forward the hypothesis that scholars who have been in the network for a longer time, have also accumulated more links. Hence, high betweenness centrality would be a result of age of a node rather than an explicit mechanism of preferential attachment. Although a tendency for 'older' nodes to have a higher probability to be (very) central is not inconsistent with the idea of preferential attachment, the results in Fig. 2 might be inflated by this.

We tested for this phenomenon by calculating the correlation coefficient between the score on betweenness centrality and the year in which the respondent reported receiving his/her Ph.D. degree. A strong negative correlation would point out that age is a strong driver of the score on betweenness centrality. The correlation coefficients can be calculated for a subgroup of 450 (of 813) respondents, data is missing for the others. The values of the correlation coefficients are −0.21, −0.15, −0.01 and −0.04, respectively, for all network relations, excluding frame of reference, excluding network relations and excluding co-authors. Although these values are negative, they do not point to very strong correlations (especially the last two values), and hence we conclude that age is not likely to be a pure driver of the results in Fig. 2.

Given that the scale-free network model seems to be a very reasonable description of the network under consideration, what can we say about Keith Pavitt's role in the network? The individual scores on betweenness centrality (as well as other potential centrality measures) indeed indicate Keith Pavitt's central role as one of the scholars to whom 'preferential attachment takes place'. In terms of the distributions in Fig. 2, Keith Pavitt is always in the rightmost tail of the graphs, among the seven 'most connected' scholars in all cases. A closer inspection of the raw data indicates that especially the large number of Ph.D. students supervised by Keith Pavitt (as well as their Ph.D. students) contribute to this central position.

5. Evolutionary economics as a community in the 'Invisible College'

The second research question identified above is concerned with the identification of subgroups in the total network. For this, the concept of lambda sets (Wasserman and Faust, 1994) is used. Lambda sets are by no means the only way of defining cohesive subgroups in a network, but there are several reasons why they are an attractive concept for present purposes. For example, lambda sets are explicitly based on the notion that a connection between two nodes in the network has implications for the *overall* connectivity of the network, i.e., beyond the two nodes that it connects directly. Also, although more than a single lambda set may exist in a network, lambda sets cannot overlap. Such overlap makes the use of other concepts (especially so-called cliques, in which overlap is often very large) difficult as a measure for distinct subgroups in the network. Finally, lambda sets are subgroups of a network in which connectivity between the members is actually high (this is not necessarily the case for other concepts, e.g. K-cores).

In order to define a lambda set, one needs to introduce the concept of 'edge connectivity' (also called 'minimum cut' or 'maximum flow'). Edge connectivity is defined between two network nodes *i* and *j*, and is equal to the minimum number of connections (edges) in the total network that needs to be cut to separate *i* and *j*. Note that if *i* and *j* are directly connected, it is usually not enough to cut the direct link between them in order to separate them, because an indirect path might exist through other, intermediate nodes. Edge connectivity is thus a measure of how tightly two individual nodes are connected: when many alternative (indirect) paths exist between them, edge connectivity will be high.

A lambda set is defined as a subset of nodes in the network for which the minimal value of internal edge connectivity is equal to a (lower) threshold value λ, and no edge connectivity between a member and a non-member of the subset is larger than $\lambda - 1$. In verbal terms, a lambda set is a subset of network nodes that is tightly connected to each other, relative to the network nodes outside the subset. The threshold level λ can be varied, and higher values of this indicate stricter definitions of the lambda sets. At $\lambda = 1$, all (connected) network nodes are in the single lambda set, while there also exists some higher finite value of λ for which all lambda sets in a network are empty. Note that the definition of lambda sets allows for the existence of multiple lambda sets in a single network. In other words, the single lambda set at level $\lambda = 1$ that comprises the whole (connected) network, may break up into separate lambda sets for higher values of λ. This feature will be used to test for the existence of (multiple) cohesive subgroups in the network. Thus, the strategy aimed at answering the second research question will be one in which the number of lambda sets in the network will be observed at all levels of λ starting at one and up to a value where all lambda sets disappear from the network.

The composition in terms of 'types of scholars' of the lambda sets that emerge in this way will also be the subject of analysis. This composition will be described in terms of the answers to the question "do you consider yourself to be an evolutionary economist?". For each lambda set, the fraction of respondents answering Yes to this question will be compared to the fraction answering No (there is also a fraction without any answer to this question, which are the people who did not actually answer the survey, but are still included, usually because they were deceased at the time the survey went out).

Referring to the research question that asks about the structure of the field under study as one in which a paradigmatic competition process goes on, one might expect that for increasing levels of $\lambda = 2$ (or more) distinct lambda sets would emerge, representing different factions in the competition process. If the label of 'evolutionary economics' makes any sense, such factions would then be broadly identifiable in terms of the answers Yes or No to the above question. An alternative hypothesis is that only a single lambda set emerges with increasing λ, i.e., with a stricter definition of cohesive subgroups in the network, a single, ever smaller, set of influential scholars remains.

The analysis was performed for the total network (corresponding to the top panel of Fig. 1) and the network that deletes all linkages based on the 'frame of reference only' (corresponding to the bottom panel of Fig. 1). For these networks, when λ is increased, the result is a single lambda set shrinking, instead of several lambda sets emerging. This is a generic property, although small lambda sets do sometimes co-exist with the large lambda set for a single value of lambda. The size (never more than three members) and number (only a very limited number of occurrences) of these lambda sets is, however, such that the one large (but shrinking with λ) lambda set completely dominates the results. Fig. 3 shows how the size of the emerging lambda sets relates to the level of λ, for both networks under consideration. Interestingly, with the exception of the leftmost part of the graph, this relation seems to follow, again, an approximate power law shape.

The result of a single lambda set rather than multiple ones is indeed an indication of a gradual core-periphery structure in the network, rather than a segmented

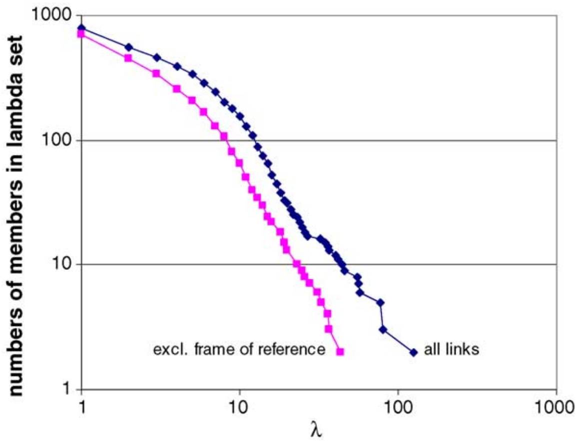

Fig. 3. The number of members of the main lambda set in the network vs. the value of λ, total network and the network excluding frame of reference links.

network as one would expect in the case of strong paradigmatic competition between different parts of the network. This result would seem to indicate a convergence, or at least co-existence, between different streams within the field of the economics of innovation and technology, rather than polarization between different schools of thought.

Where does this leave us with regard to the position of evolutionary economics in the broad field? In order to answer this question, Fig. 4 presents the composition of the lambda sets for both networks in terms of the answers to the question “do you consider yourself to be an evolutionary economist?”

The composition at $\lambda = 1$ corresponds to the total network, although nodes that are disconnected from the main component are excluded. It can be observed that the largest fraction of respondents (around 55% in both cases) testifies not to be an evolutionary economist, while 30–35% does feel to be an evolutionary economist. The remainder (labeled ‘nothing’ in the legend) consists of network members who did not answer the questionnaire, and hence show no answer for this question. In other words, evolutionary economists are a minority in our sample. It must be noted, however, that non-evolutionary network members are not identified in a ‘positive’ way, and hence no conclusions on the cohesiveness of this subgroup can be drawn.

The interesting feature in Fig. 4 is the relatively large role of evolutionary economists in the evolving (with λ) lambda sets. Starting from $\lambda = 1$, the share of evolutionary economists in the lambda set increases, indicating that more non-evolutionary than evolutionary economists drop out of the cohesive subgroup at stricter levels of identification (λ). This increasing share of evolutionary economists holds until levels of λ slightly above 10, after which the composition more or less settles down.

One may conclude from this that the label ‘evolutionary economics’ is a relevant one for describing the core of scholars in the field of the economics of innovation and technology. Among the most well connected scholars in the network (the rightmost part of the distributions of connectivity in Fig. 2, and the ones remaining longest in the lambda sets describing the core of the network) are relatively many who consider the label ‘evolutionary economics’ as a reasonable one describing their activities. Thus, our results suggest that rather than ‘evolutionary economics’ being one of the factions in a paradigmatic battle in the field, this label is a reasonable, although admittedly not perfect, description of the core group of scholars around which the field organizes itself. However, we must bear in mind that due to the potentially biased nature of our sample, and because of the fact that the ‘non-evolutionary’ part of the network is in fact a rather heterogeneous group,

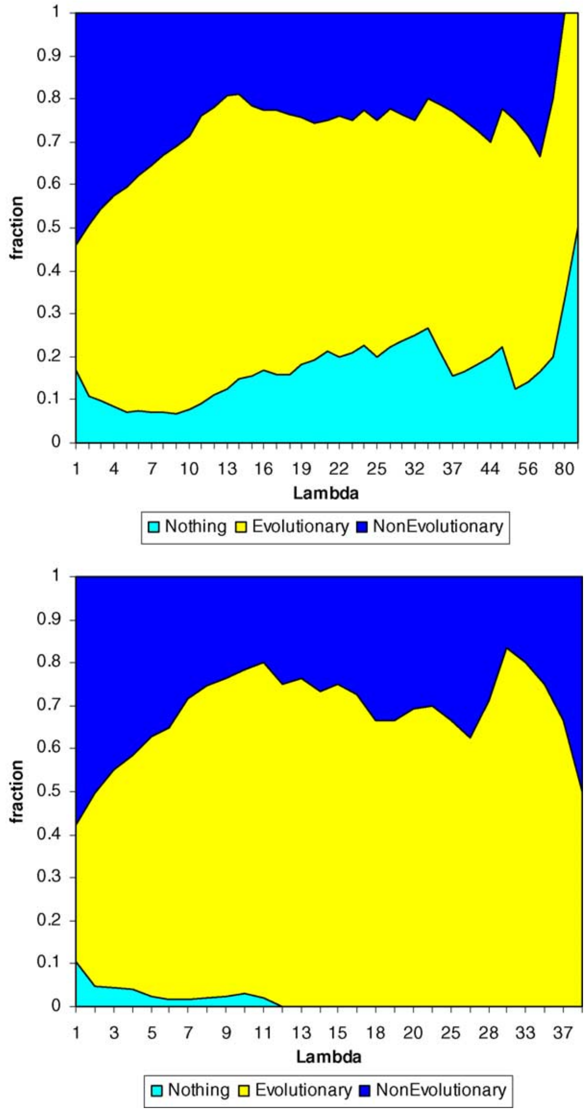

Fig. 4. The evolution of the composition of the lambda sets with λ, total network (top panel) and network excluding frame of reference (bottom panel).

we cannot take these results as the final verdict on the non-existence of paradigmatic struggles.

Finally, where does Keith Pavitt stand in the lambda set analysis? Although it will not be revealed whether or not Keith Pavitt considered himself as an evolutionary economist, the raw results show that in both cases, Keith Pavitt is one of the scholars remaining in the lambda set longer than almost all other scholars in our analysis.

6. Conclusions

The analysis of the research community of the economics of innovation and technology that was undertaken on the basis of a survey in the field suggests two major conclusions. First, the network of scholars in this field may be characterized as a scale-free network, which suggests that the main factor in the evolution of the network is preferential attachment in a growing network context. Preferential attachment refers to the tendency that new members of the network (i.e., young scholars entering the field) prefer to build linkages to scholars that already have a high reputation in the field. Such a tendency is consistent with the so-called Matthew effect in science dynamics, which is a tendency describing increasing returns to scale to scientific production. Highly reputable scholars attract more resources (which, in the current case, could be an abstract notion such as 'network capital'), and thereby gain even more in terms of reputation. The power law distribution of connectivity in the networks of collaboration and interaction observed in this paper suggests that this is an important factor in network evolution of the field. This tendency has also been observed in other contexts of scientific collaboration (e.g., Wagner and Leydesdorff, 2004; Newman, 2001).

The second conclusion is that the field does not seem to evolve in a mode of competition between different paradigmatic approaches to the object of study. A superficial reading of the critique to mainstream economics by some of the more active scholars in the field, might suggest that such a paradigmatic battle is taking place. In the analysis here, this was operationalized by means of the identification of so-called cohesive subgroups at various levels of strictness of the definition. When stricter definitions of cohesive subgroups were applied, a single core group in the network remained intact (although with an ever-smaller number of members). This is taken to indicate that only a single core set of scholars may be found in the field. The alternative would have been that the network breaks up into competing factions, embodying different sides of the paradigmatic battle, but this is not supported by the data. It was also found that scholars who consider the label 'evolutionary economics' as relevant for describing their work are overrepresented in the core of the network (as defined by the single cohesive subgroup).

Together, these results paint a picture of the field of the economics of innovation and technology as an emerging field that is organized around a limited number of highly connected, and intellectually leading scholars. Keith Pavitt was shown to be one of these intellectual leaders who continue to act as a guide for the rest of the field. Evolutionary economics is a reasonable, although not perfect label describing this core group.

The results suggest at least four paths for further research. First, it may be interesting to see how the network structure based on the survey database explored in this paper differs from a network based on publications or citations. Such more formal and codified network channels may provide a different result, for example, because of editorial policies of journals (e.g., some journals may be more committed to the evolutionary core of the field than others). Second, the exact nature of the power law distributions (estimated slope) observed in connectivity of the network members may be investigated using more robust statistical tools. This will enable a more precise identification of the network properties, as well as the stylized factors behind the network formation dynamics. Third, it will be interesting to compare more systematically the network described in this paper with similar networks in other fields in science. Fourth and finally, a more direct test of the preferential attachment mechanism would be useful to assess the applicability of the scale-free networks model at the microlevel.

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